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Understanding Climate Uncertainty with an Ocean Focus

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Understanding Climate Uncertainty with an Ocean Focus

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- Introduction & Motivation
- Uncertainty Methodology
- Designing the Experiment
- Ocean Metrics
- Early Outcomes

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Motivation

Feasibility Study:

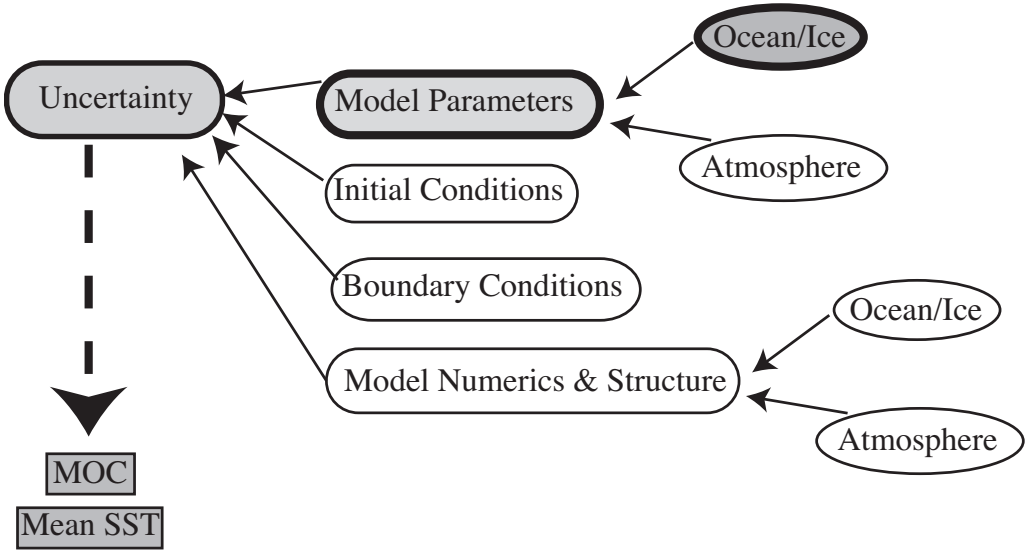
- Can statistical analysis of computer experiment methods* be used to understand uncertainty in complex climate GCMs?

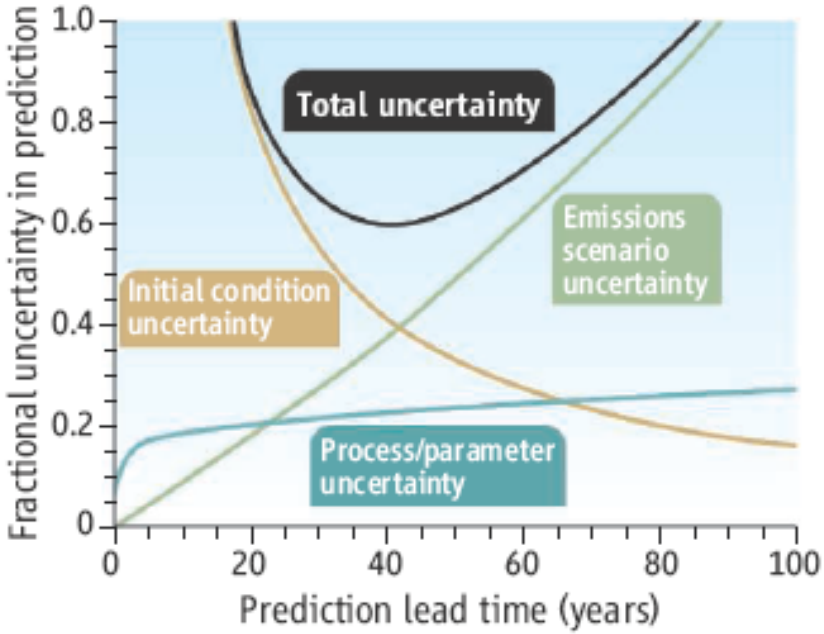
- To limit computation time and complexity, study will only examine the ocean/ice components of a climate model

- Collaboration of Statisticians and Physical Oceanographers

* BACCO: Bayesian Analysis of Computer Code Output
* DACE: Design and Analysis of Computer Experiments

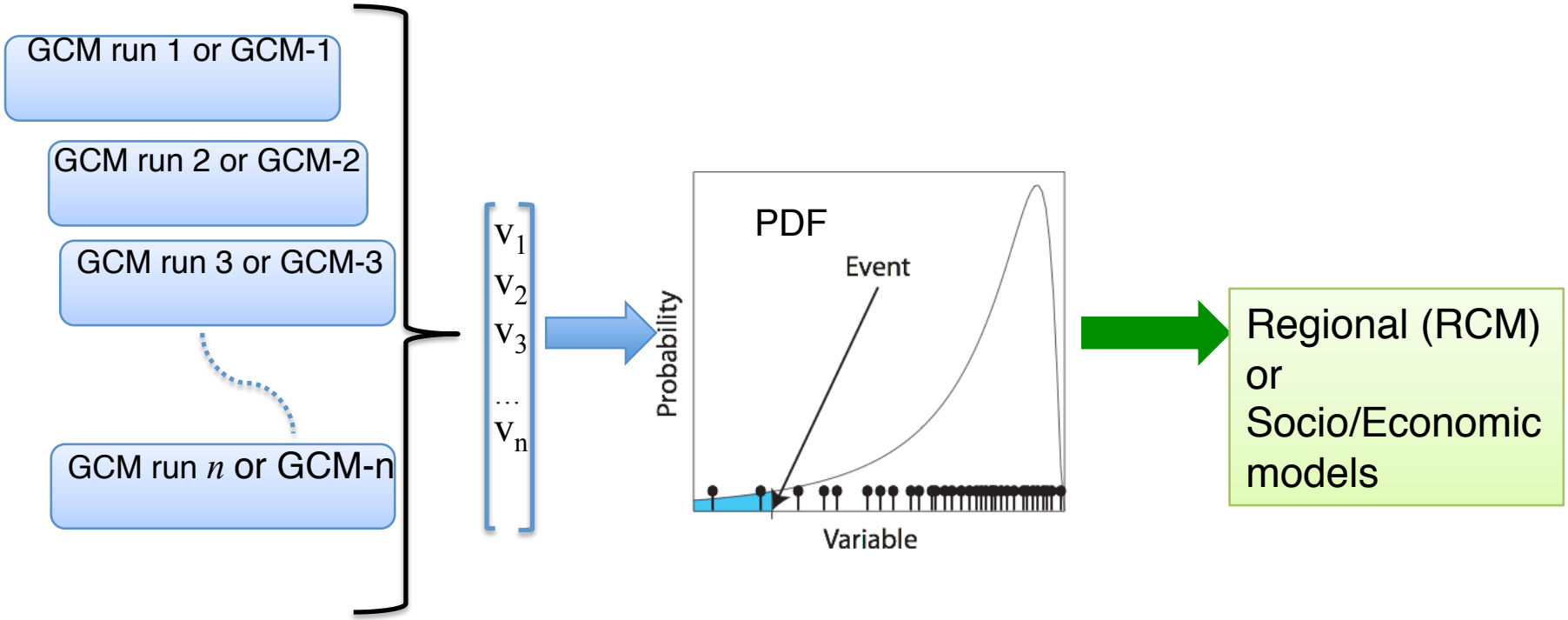
Uncertainty sources in a GCM





Cox and Stephenson, Science 2007

Uncertainty and flow of information



Method 1: Monte Carlo Methods → Very Large Complex Model Ensemble

GCM run 1
With parameter array X_1: $[x_1, x_2, x_3 \ldots x_{10}]$

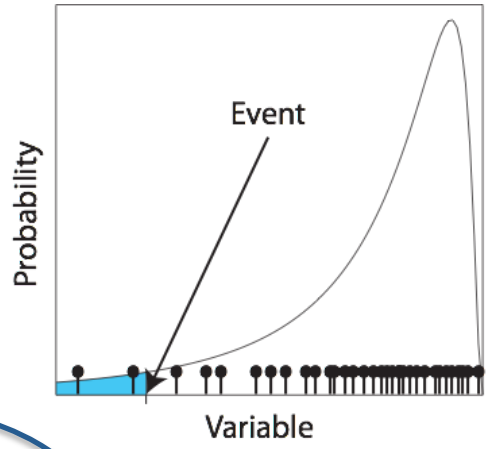
GCM run 2
With parameter array X_2: $[x_1, x_2, x_3 \ldots x_{10}]$

GCM run 3
With parameter array X_3: $[x_1, x_2, x_3 \ldots x_{10}]$

GCM run n
With parameter array X_n: $[x_1, x_2, x_3 \ldots x_{10}]$

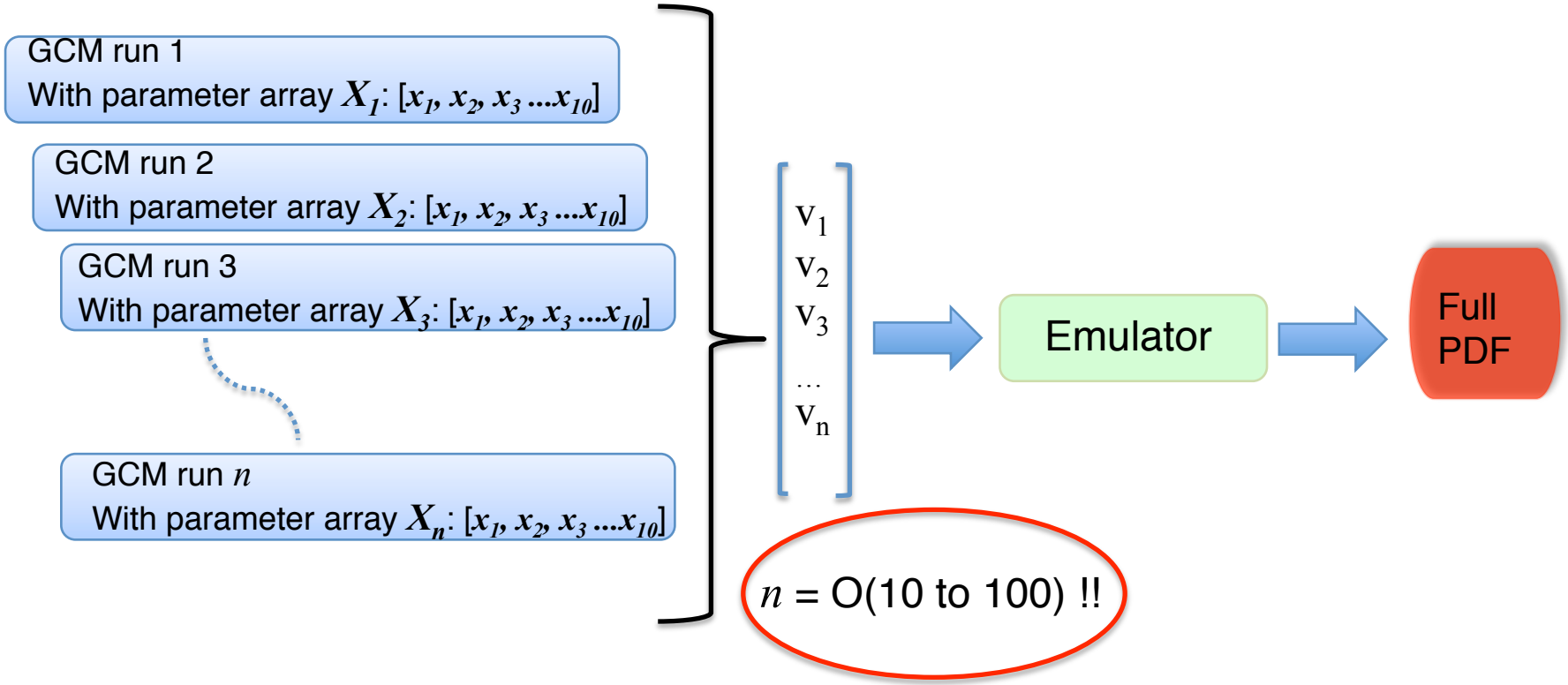
$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \cdots \\ v_n \end{bmatrix}$$

Full PDF



n = O(10,000)

Method 2 – Complex model + emulator

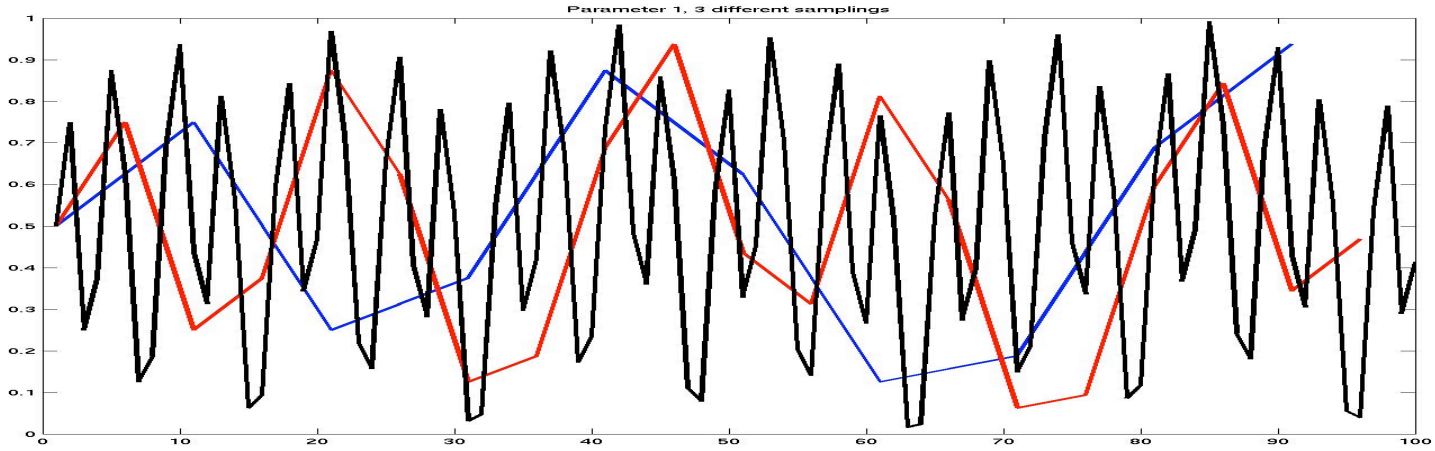


Design of Ensemble

Goal: Create a set of parameters that sample the model space adequately

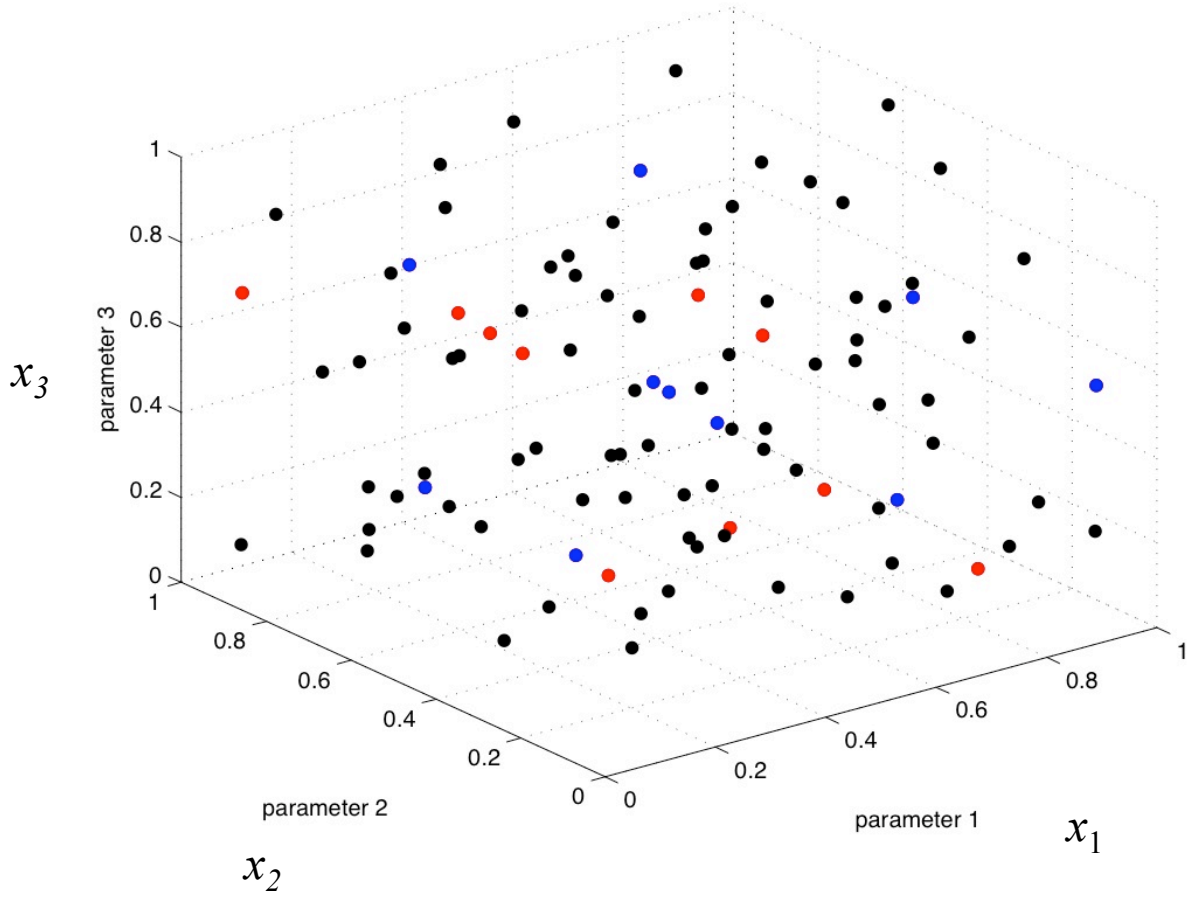
- Method: Use Sobol Sequence or Latin Hypercube methods to span parameter space to reduce the number of simulations required.

[Santner TJ, Williams B, Notz W., 2003, The design and analysis of computer experiments. New York: Springer]



Blue 10 runs
Red 20 runs
Black 100 runs

Sobol Sequences



- Determine min/max values of each parameter
- Set appropriately using scale from 0 →1

Emulator Details

Given a climate model: $Y = F(x)$; with vector x as tunable inputs

Use a "small" set of simulations or runs, varying the values of x

To build an emulator, $f(x)$, with the following characteristics:

- reflects the true value of Y at points x
- at other points, the distribution of $F(x)$ should give a mean value for $F(x)$ that represents a plausible value of Y given any vector x
- the probability distribution should be a realistic view of the uncertainty in the approximation to the full model.

$$F(x) \sim f(x) = GP(m(x) = 0, k(x, x'))$$

Truth (metric)

estimate

$$= m_0(x) + GP(k(x, x'))$$

Mean process

$$m_0(x) = h(x)^T b$$

q coefficient vector

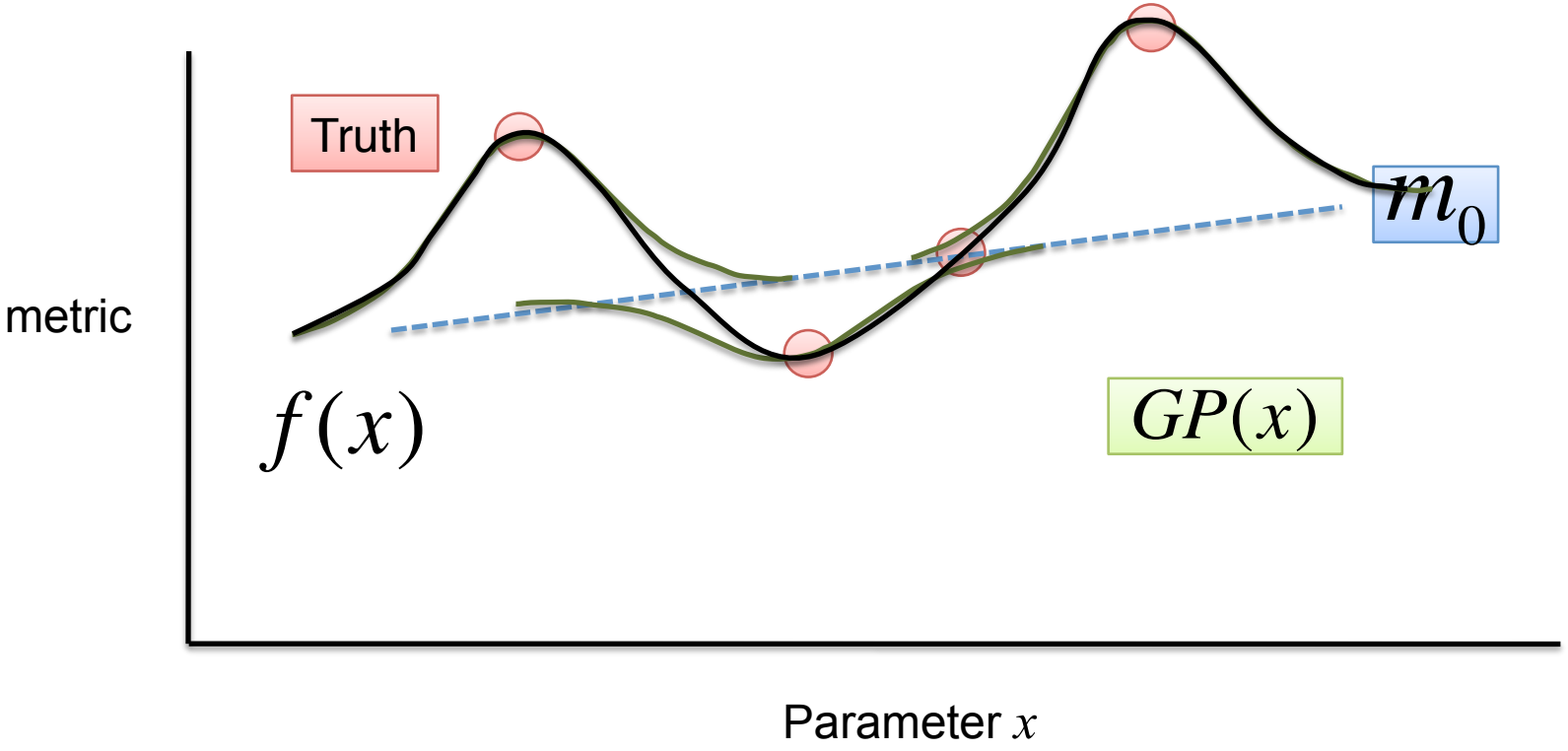
vector of *q* regression functions

Gaussian process

$$GP(k(x, x')) == \sigma^2 e^{(-(x_1 - x_2)^T B(x_1 - x_2))}$$

Variance

A covariance function, in this case, a Gaussian covariance which assumes stationarity

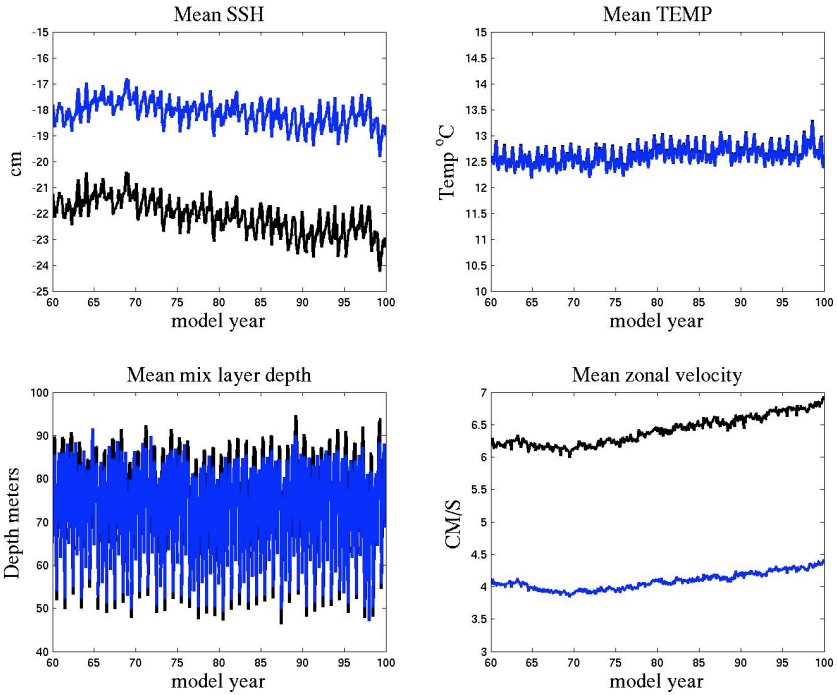

Truth
m_0
metric
$f(x)$
$GP(x)$
Parameter x

GCM details

- CCSM3 x3 (~ 3 degree resolution)
- Active ocean/ice components (POP2 & CICE)
- NCEP inter-annual reanalyzes forcing
- 9 parameters (x)
- Initial Design Phase (10 runs): design locations
- Full experiment phase (100 runs)

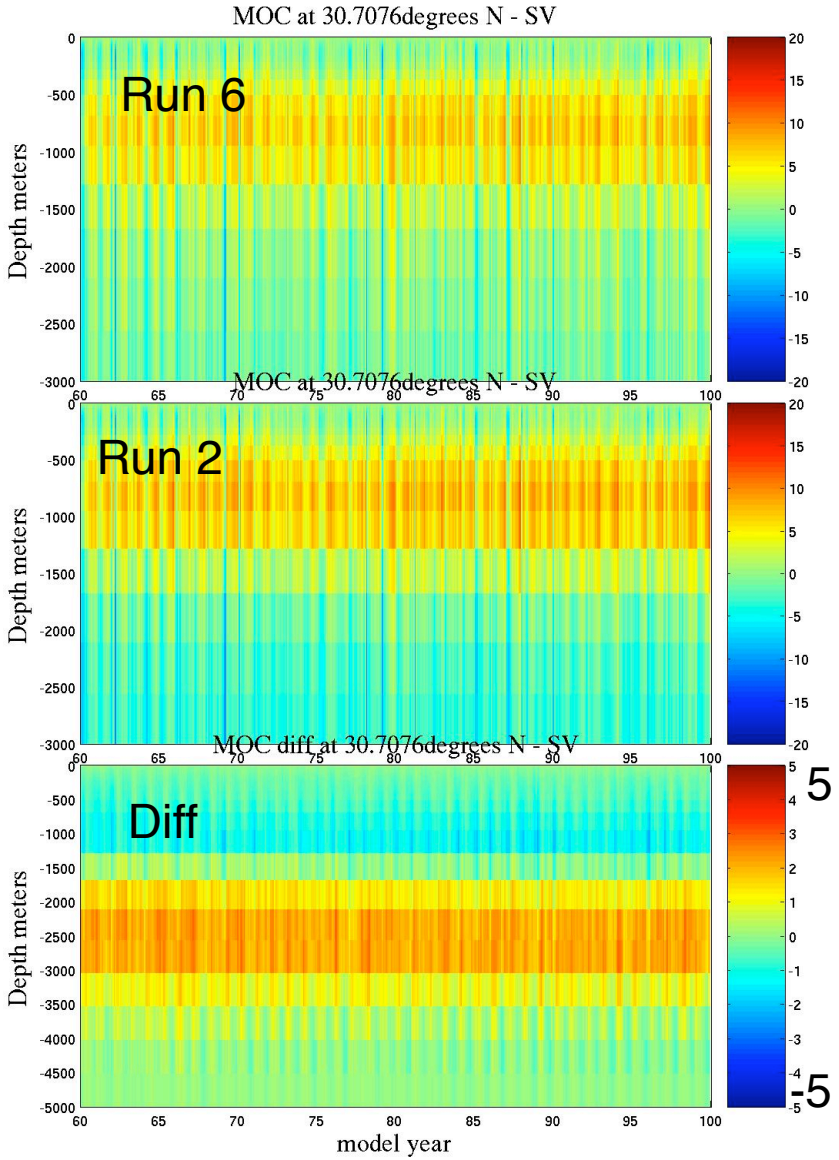
Examples of metrics to be examined

- SST – regional and global; mean and variance
- Mixed layer depths
- Transports – Heat, volume; across basins, passages
- Heat Content
- Current strengths, locations
- Meridional overturning strength



Run 6

Run 2



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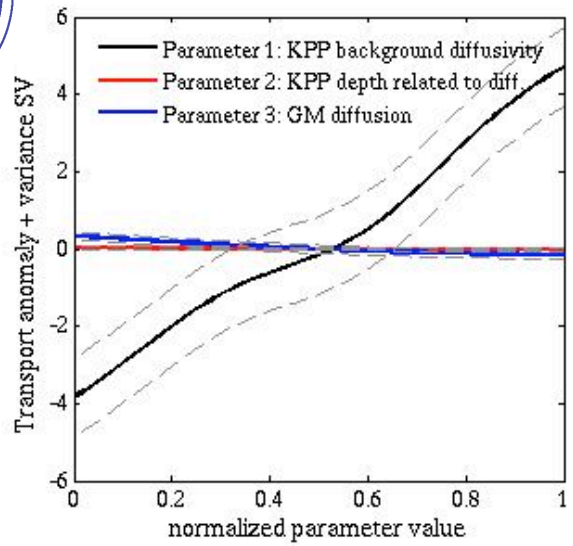
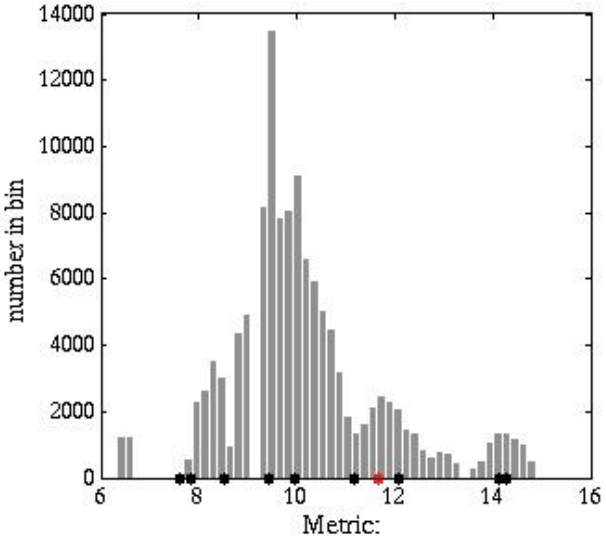
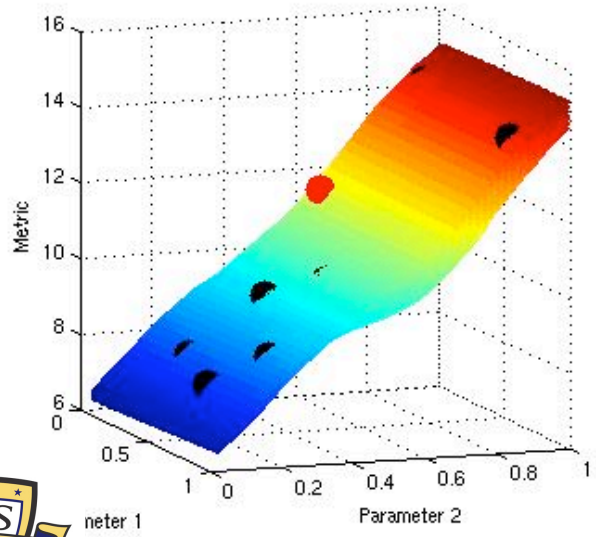
Atlantic Meridional Overturning







- GM diffusion same order as KPP diffusivity; (uncertainty greater for KPP parameter)
- Broad distributions of likely values

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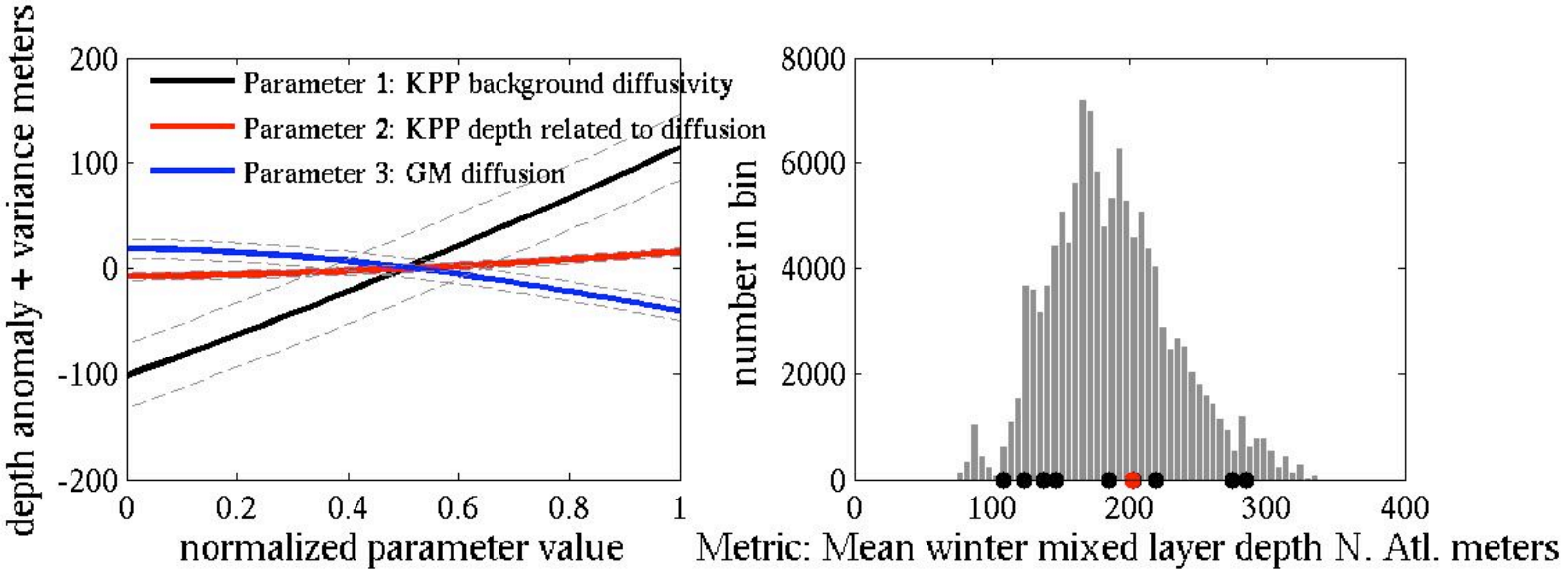
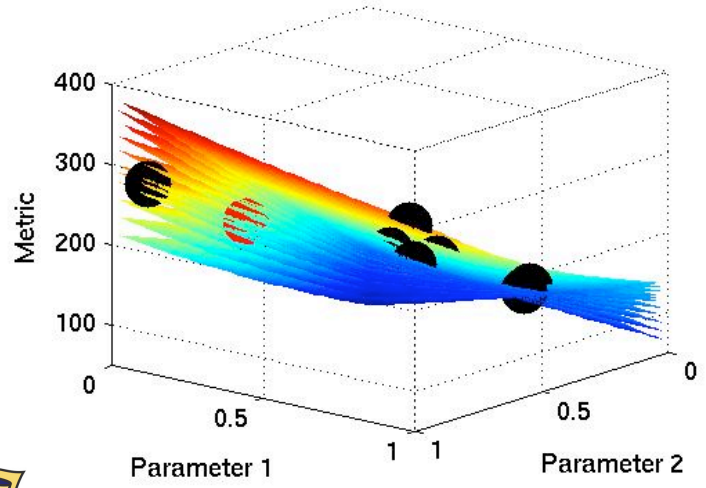
North Atlantic Winter Mixed Layer Mean Depth





- KPP diffusivity parameter dominant
- Linear
- Most likely value ~170m
- Mean value ~ 210m

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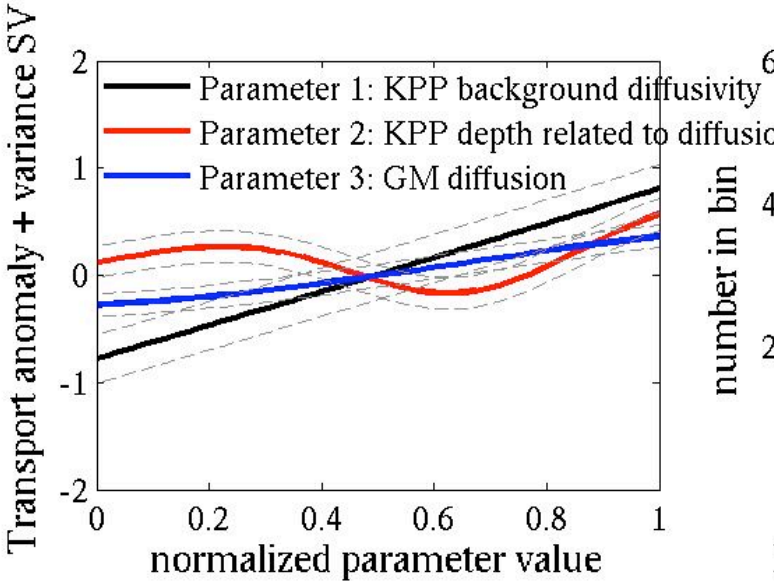
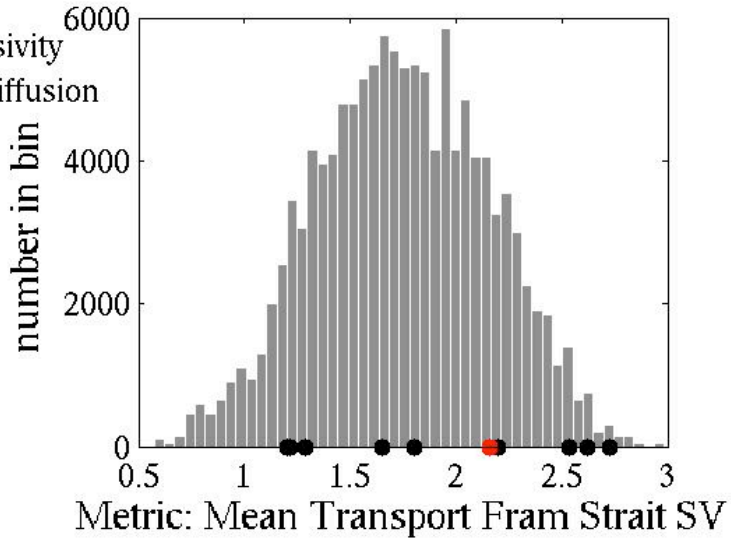
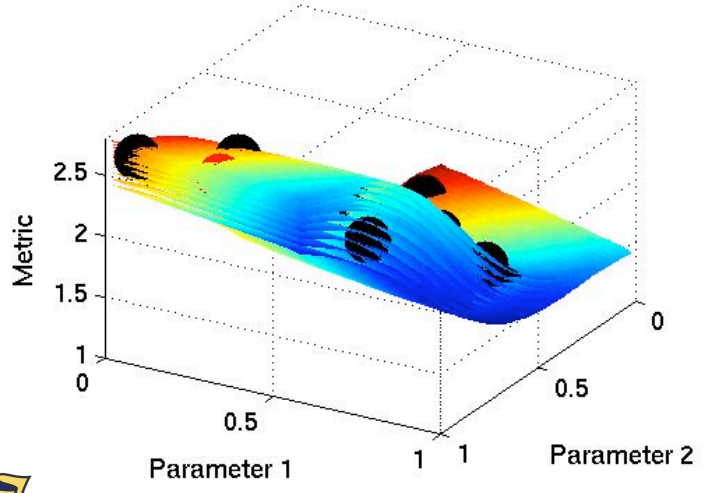
Mean Transport: Fram Strait







- KPP diffusivity and the depth parameter same order of importance
- Linear & non-linear response
- Most likely value ~1.6SV

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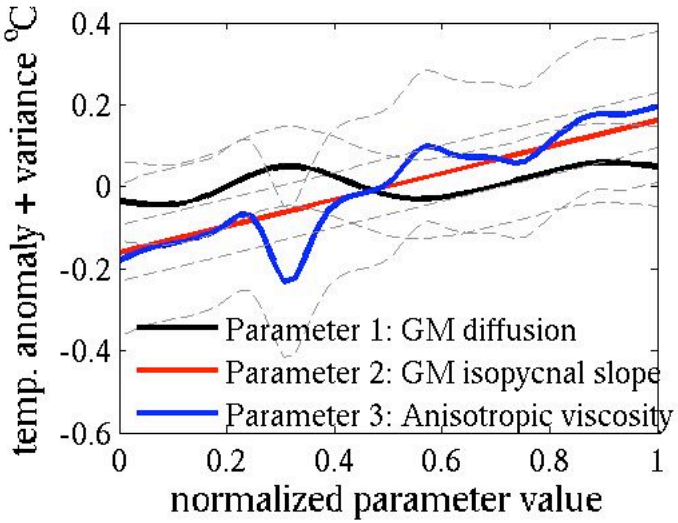
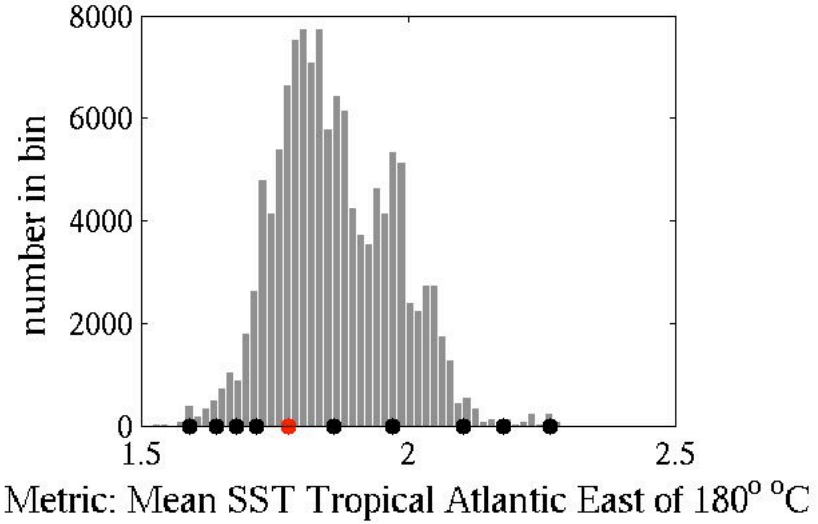
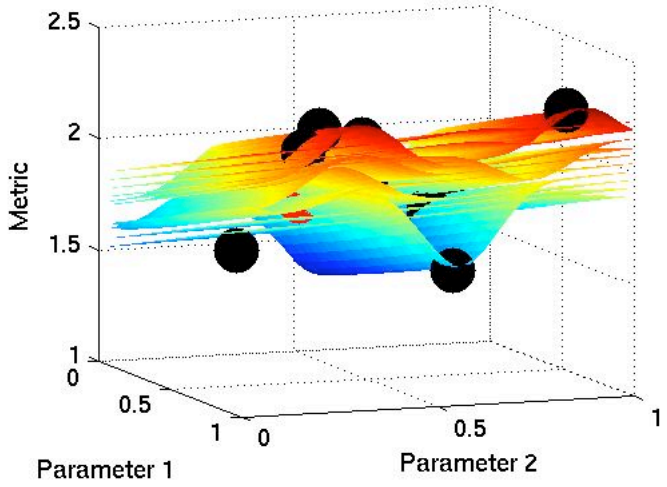
Tropical Atlantic SST (annual cycle removed) – East of 180°







- Competing non-linear parameters
- Large uncertainties in all parameters
- Most likely value ~1.75 °C
- Mean ~1.9 °C

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Conclusions

- Initial design phase shows that experiment design is adequate to test uncertainty within the parameter space of a GCM.

- Both linear and non-linear parameter effects on a metric can be separated

- Parameter influence on a metric has also been demonstrated.

- Metric uncertainty determination has be demonstrated

- Next step is to complete the full 100 member ensemble, followed by emulator creation for the full 9 parameter space

Thank you for your attention

References:

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•Gattiker,J., 2005, Using the Gaussian Process Model for Simulation Analysis Code, Los Alamos technical report LA-UR-05-5215.

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•O'Hagan, A., 2006, Bayesian analysis of computer code outputs: a tutorial. *Reliability Engineering and System Safety,* **91**, 1290–1300.